

Detection of Indonesian wildlife sales and promotion through social media using machine learning approach

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ABSTRACT

Social media is one of the communication media that is widely used in the digital era as it is today. The use of social media allows people who are far apart to communicate and exchange media, both voice, video, and images quickly and even in real-time. In the past, the sale of protected animals was mostly done on the black market, usually involving a supply chain between sellers that usually existed in traditional markets or certain communities. With the existence of social media, the trend in conducting transactions and promoting wild animals has shifted from traditional to modern thanks to the support of existing technology. Protected wild animals are of concern to the local government or the global world to protect their existence. Therefore, this research proposes a machine learning (ML) based approach to detect the promotion and sale of wild animals on social media. The implementation of Naïve Bayes classifier (NBC) has a high accuracy in detecting trade in wild animals on social media with an accuracy value of 86. The implementation of ML-based approach is expected to produce new technology that allows authorities to know and monitor social media in order to reduce the sale and promotion of protected wildlife.

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1. INTRODUCTION

Wildlife crime is a big business that threatens the existence of wildlife. This business is run by a malicious international network [1]. Trafficked wildlife is the same as in cases of illegal drug and weapons trafficking. Based on data from traffic, which is a wildlife monitoring network, it is almost impossible to determine with certainty how much wildlife trade is illegal. The value of the wildlife trade business can reach billions of dollars [2], [3].

Some examples of illegal wildlife trade include the hunting of elephants for their tusks, tigers for their bones, whiskers, skins, and the hunting of Javanese monkeys as pets. There are still other excessive exploitation by criminal networks such as exploitation of turtles to pangolins to be used as drugs. The wildlife trade has been critical and continues to increase with demand [4], [5]. This increasingly threatens the existence of wildlife and the balance of the ecosystem.

There are several places in the world where wildlife trade is massive. These places are called wildlife trade hotspots including the international border of the Republic of China, the area of East and South Africa, Southeast Asia, Papua New Guinea, the Caribbean, Mexico, and the eastern border of the European

Union. Moreover, physical trading with direct buying and selling mechanisms has been supported by the existence of social media. Social media has become a new vehicle for wildlife traders in conducting sales business processes [6], [7]. On social media they can upload photos of wildlife and certain texts, create private groups, and communicate freely.

The use of social media by criminals of illegal wildlife trade can reach directly to areas of location close to wildlife habitat. Through social media, the flow of illegal wildlife demand has shown a sharp increase to date [6], [8], [9]. Along with the rampant development of social media, almost all levels of society can operate social media for illegal wildlife trade. The process of buying and selling rare and protected wildlife through social media is very fast, going beyond the process of enforcing the wildlife trade law itself. The modus operandi of using social media for wildlife trafficking is also growing rapidly. Actors can easily change the trade route, transaction location, and can change their identity.

Social media which is usually used to communicate has become a forum and supporting tool for thousands of illegal wildlife traders. In social media, they market, connect, negotiate, and even accept payments. This is a new challenge for both researchers and agencies responsible for reducing wildlife trade [10]. In this study, the use of machine learning (ML) algorithms is proposed to track wildlife sale content.

Xu *et al.* [11] conducted research by utilizing ML in tracing the traces of wildlife sales. This research uses a bitter topic model which consists of 4 phases, namely manual search, data collection, data processing, and data analysis. This research is devoted to finding the sale of elephant and pangolin tusks which are classified as critically endangered (CE) animals. Unfortunately, this research only uses terminology in English even though the hotspots for selling protected wild animals do not use English but the local language. So, it is possible that the search results will be less. Hotspots for selling protected wildlife include China, Indonesia, the Andes Mountains, and Kenya [12]. In this research, the terminology or keywords are written in Indonesian language as Indonesia is one of wildlife crime hotspot.

2. METHOD

2.1. Machine learning and Naïve Bayes classifier

ML is a technique that allows machines to be developed to learn a pattern independently [13]. ML is a combination of statistics, mathematics, and data mining, in practice machines can learn to analyze without the need for reprogramming or a command. It can acquire data, studying it, and performing specific tasks. The tasks that ML can perform also vary, depending on what is being studied. Therefore, ML can support almost all branches that require problem solving.

The role of ML helps humans a lot in performing tasks [14]. In its implementation, without us realizing it can be found easily in our daily lives. For example, when we use the fingerprint feature on a smartphone, or when we access weather predictions.

There are two basic techniques of ML, namely supervised and unsupervised learning [15], [16]. Supervised learning techniques can be applied to learning that can capture information in the data by giving certain labels, while unsupervised learning does not use labels to predict a variable. What is done is to see the similarities of each variable that is owned. If the variables have similarities, then clustering will be carried out. The number of clusters can be unlimited.

In ML there are several methods including linear regression, decision tree, support vector machine (SVM), Naïve Bayes classifier (NBC), k-nearest neighbors algorithm (KNN), and K-means. In this study, NBC is used. NBC is a ML algorithm which implement Bayes theorem to classify data [17]. Due to its simplicity and efficiency, NBC is widely used in text classification. NBC is also offers competitive performance compare to other classification method [18]. The advantage of using Naive Bayes is that this method only requires a small amount of training data to determine the parameter estimates needed in the classification process. Naive Bayes often works much better in most real-world situations complex than expected [19]. Another advantage is the fast calculation [20] and simple and high accuracy algorithm [21]. Also, NBC can handle missing values by ignoring instances during odds estimation calculations [22]. In (1) shows the calculation of probability using Bayes theorem:

$$P(a|b) = \frac{P(b|a)P(a)}{P(b)} \quad (1)$$

where the probability that we are interested in calculating $P(a|b)$ is called the posterior probability and the marginal probability of the event $P(a)$ is called the prior.

2.2. Research method

In this part, research methodology is described in detail. Figure 1 shows the research method. In this research, wildlife trade data were collected from twitter. Data were collected using keywords that indicate the

occurrence of wildlife trade, such as “jual kulit harimau”, “WTS landak”, and “kulit macan tutul”. This process obtained 2,700 tweets which grouped into wildlife life trade and non-wildlife trade category. Based on the result of labelling process, the number of tweets that identified as wildlife trade and non-wildlife trade category is 970 and 1,730 respectively. The dataset is splitted into data training and data testing with the proportion of 80% and 20% respectively.

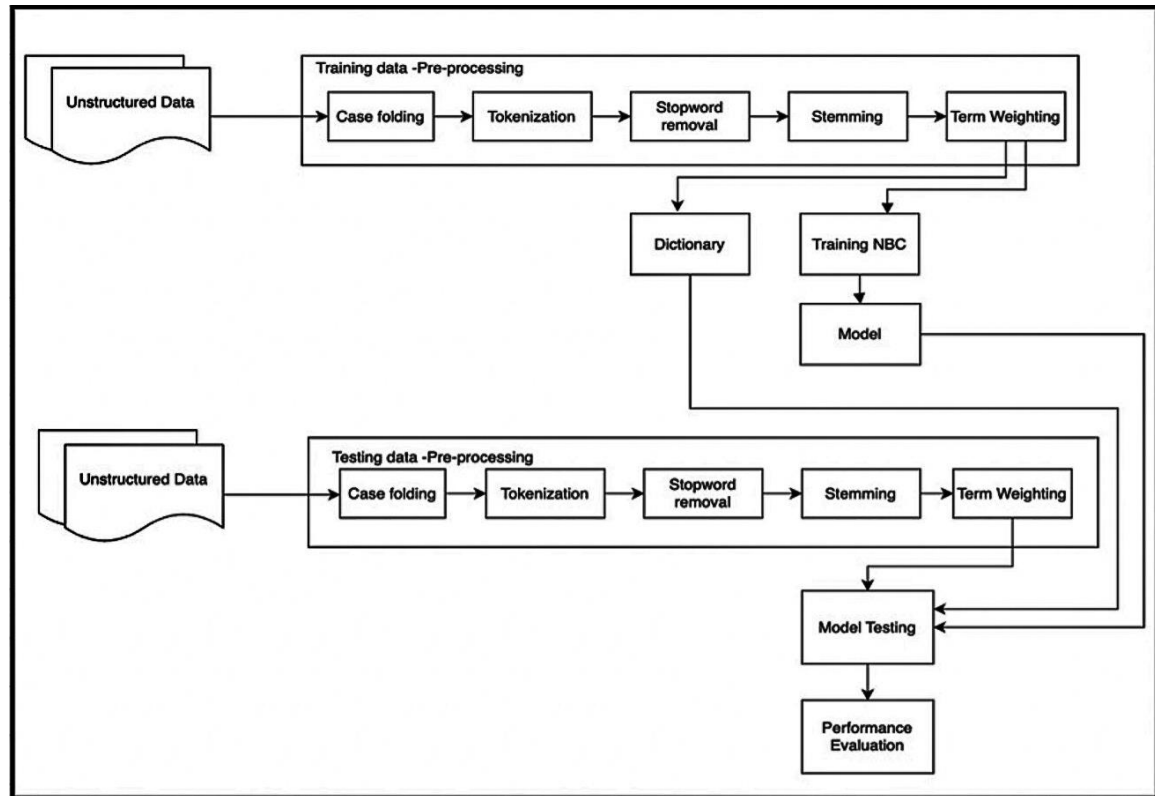


Figure 1. Research method

The next phase is data pre-processing which consist of noise removal and feature extraction. There are 4 processes employed to remove the noise from wildlife trade data. Casefolding process conducted by turning the datasets into lower case text in Figure 2. Tokenization process is done by removing numbers, punctuation, whitespace leading, whitespace trailing, and multiple whitespaces in Figure 3.

The next process is stop words removal which conducted by removing all words that are frequently used in the text but do not contain meaningful information to classify the text in Figure 4. In this process, the Indonesian natural language tool kit (NLTK) corpus stop word is used. In addition, the stop word list is defined in addition to the NLTK stop word corpus. The last process is stemming in which affixes, prefixes, and suffixes are removed from each word so that the root word is obtained.

After removing noise from the data, the next step is feature extraction. In this phase, textual data are transformed into a numerical data using term weighting. Term is a word or phrase in a document that can be used to identify the context in the document itself. Often the emergence of terms in documents can be used as a process to perform calculations so that it is known whether a word is important or not.

```

# ----- Case Folding -----
# using lower() function
Casefolding_result = sentence.lower()
  
```

Figure 2. Case folding process

```

#----- Tokenizing -----
#Remove Numbers
lowercase_sentence = re.sub(r"\d+", " ", casefolding_result)

#Remove Non Alphanumeric characters
lowercase_sentence = re.sub(r'[^a-z\s]+', ' ', lowercase_sentence)

#Remove Punctuation
lowercase_sentence = lowercase_sentence.translate(str.maketrans("", "", string.punctuation))

#Remove Leading and Trailing Whitespace
lowercase_sentence = lowercase_sentence.strip()

#Remove Multiple Whitespace into Single Whitespace
lowercase_sentence = re.sub('\s+', ' ', lowercase_sentence)

tokens = nltk.tokenize.word_tokenize(lowercase_sentence)

```

Figure 3. Tokenization process

```

#Stop Words Removal
list_stopwords = nltk.corpus.stopwords.words('indonesian')
stopword_tambahan = ['yg', 'gitu', 'aja', 'gini', 'ajah', 'kalo', 'ah', 'nihhh', 'hahaha', 'wkwwkw', 'deh', 'or', 'sih']
list_stopwords.extend(stopword_tambahan)
tkn_no_stopwords = [word for word in tokens if not word in list_stopwords]

#---Stemming
factory = StemmerFactory()
stemmer = factory.create_stemmer()
list_tokens = tkn_no_stopwords
output = [(stemmer.stem(token)) for token in list_tokens]
return output

```

Figure 4. Stop words removal and stemming process

In this study, term frequency–inverse document frequency (TF-IDF) weighting technique is employed. Term frequency (TF) shows the number of a word's occurrence in a document over the total number of words in the document. The calculation of TF value can be done using (2):

$$TF(w, d) = \frac{\text{frequency of word } w \text{ in document } d}{\text{number of words in document } d} \quad (2)$$

Inverse document frequency (IDF) reflects the importance of a word based on its occurrence in documents. In contrary to TF, according to IDF calculations, the more occurrences of a word in a document, the lower its importance [23]. In (3) shows the formula to calculate IDF:

$$IDF(w) = \log \frac{N}{n} \quad (3)$$

where N is the number of documents and n the number of documents which contain the word w . The TF-IDF value is obtained from the multiplication of TF and IDF.

2.3. Performance evaluation

In this study, confusion matrix is used as a tool for performance evaluation as in Figure 5. Some measurements techniques are employed, namely accuracy, precision, recall, and F-measure. Accuracy is a measurement to determine the proportion of the correctly classified data over total number of data [24]. As can be from as (4), accuracy can be calculated by dividing the number of data that was correctly predicted (true positive (TP) and true negative (TN)) by the number of all testing data.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

Precision describes the ratio of predicted positive data that are correctly classified to the number of positive data. Precision is obtained by dividing the number of TP cases by TP and false positive (FP) cases as (5):

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Recall is the proportion of positive data that correctly classified. Recall reflects the ability of a model to correctly classify positive cases. As can be (6), recall is generated by dividing TP cases by TP and false negative (FN) cases:

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

The F-measure is derived from the precision and recall values as described (7). It is difficult to compare a high recall value with a low precision value, or vice versa. As a result, the F-measure would assist in balancing the measurement between precision and recall value [25].

$$F - measure = \frac{2 * recall * precision}{recall + precision} \quad (7)$$

		Actual Values	
		Positive	Negative
Predicted Values	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative

Figure 5. Confusion matrix

3. RESULTS AND DISCUSSION

In this part, the result of wildlife trade classification using NBC is described and evaluated. Table 1 shows the confusion matrix for wildlife trade classification. The classification model predicted 363 data correctly from a total of 540 data, which consist of 130 wildlife-trade data and 333 non-wildlife trade data. Meanwhile, there are 77 data that are predicted incorrectly.

Table 1. Confusion matrix

		Actual		Total
		True	False	
Predicted	True	130	62	192
	False	15	333	348
Total		145	395	540

Accuracy, precision, recall, and F-measure is employed as classification model performance measurement. In Table 2, the accuracy of wildlife trade classification model is 0.86. This result indicates that wildlife trade classification model can correctly classified 86% cases over all the given cases. Precision and recall value in wildlife trade classification model are 0.68 and 0.90 respectively. In this study, precision value is significantly lower than any other performance measurement. Low precision show that the classification result has many FP case. This condition indicates that the classification model have lower ability in predicting the non-wildlife trade data into the right category. Meanwhile based on recall value, classification process produces a very small amount of FN. This condition indicates that the classification model has a high ability to correctly classify wildlife trade data. The value of F-measure in this study is 0.77 which indicates that the precision and recall value are quite balance.

Table 2. Performance measurement

Performance indicator	Value
Accuracy	0.86
Precision	0.68
Recall	0.90
F-measure	0.77

4. CONCLUSION




This paper proposes a ML-based approach to detect the promotion and sale of wild animals on social media. NBC is employed to determine the probability of wildlife trade data. The datasets were collected from Twitter. The result shows that the implementation of NBC can classify wildlife trade data with 86% of accuracy. The dataset used in this study was in the Indonesian language so it has weaknesses due to the use of informal languages, local languages, and foreign languages. Therefore, for further research, we will explore data preprocessing considering that the accuracy of the model is strongly influenced by the quality of the data.

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